Characterizing Evaluation Practices of Intrusion Detection Methods for Smartphones

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Abstract

The appearance of a new Android platform and its popularity has resulted in a sharp rise in the number of reported vulnerabilities and consequently in the number of mobile threats. Mobile malware, a dominant threat for modern mobile devices, was almost non-existent before the official release of the Android platform in 2008. The rapid development of mobile platform apps and app markets coupled with the open nature of the Android platform triggered an explosive growth of specialized malware and subsequent search for effective defence mechanisms. In spite of considerable research efforts in this area, the majority of the proposed solutions have seen limited success, which has been attributed in the research community to the lack of proper datasets, lack of validation and other deficiencies of the experiments. We feel that many of these shortcomings are due to immaturity of the field and a lack of established and organized practice. To remedy the problem, we investigated the employed experimentation practices adopted by the smartphone security community through a review of 120 studies published during the period between 2008–2013. In this paper, we give an overview of the research in the field of intrusion detection techniques for the Android platform and explore the deficiencies of the existing experimentation practices. Based on our analysis

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we present a set of guidelines that could help researchers to avoid common pitfalls and improve the quality of their work.

Keywords: intrusion detection, smartphones, mobile malware.

1 Introduction

The rapid evolution of various mobile platforms in the past decade has swiftly brought smartphones to all aspects of our daily life. Such popularity has stimulated underground communities, giving an unprecedented rise to mobile malware. Among the most targeted platforms is the Android platform, mostly due to the ease of use of malicious apps, and the lack of proper defence. According to Kaspersky's estimation, the number of mobile malware targeting the Android platform tripled in 2012, reaching 99% of all mobile malware [37]. Also, they said that in 2013 there are more than 148,427 mobile malware modifications in 777 families and 98.05% of mobile malware found this year targets Android platform [41].

The lack of necessary defence mechanisms for mobile devices has been mostly restricted by the limited understanding of these emerging mobile threats and the resource-constrained environment of smartphones. Indeed, on the one hand, the rapid growth of vulnerabilities for a new and less-studied platform, coupled with the lack of timely access to emergent mobile malware, hinder our abilities to analyze these threats. On the other hand, the resource-constrained environment of smartphones, which is unable to afford computationally intensive operations, presents a significant challenge to the development of intelligent intrusion detection solutions. With mobile phone security quickly becoming an urgent necessity, researchers have started focussing their attention on the problem.

In the past several years the number of studies in the field of mobile phone security has been steadily increasing. In light of recent work around security-related studies in long established domains (e.g. anomaly detection), a lack of scientific rigor has been shown in the experimentation in the majority of these studies [42–43, 47]. As a result, we examine the evaluation practices of a newly appearing field of mobile phone security.

In this paper, we explore research in the area of intrusion detection for the mobile platform published during the period between 2008–2013. Aiming to discover the problems related to experimentation rigor encountered in other fields, we highlight the most common shortcomings and offer a set of guidelines for proper evaluation practice to the smartphone intrusion detection

community. Within this study we give an overview of the common trends in smartphone intrusion detection research highlighting the general focus of the research efforts and the existing gaps. We hope that these efforts will give an insight into the future development of viable intrusion detection mechanisms for mobile devices.

The rest of the paper is organized as follows: in Section 2, we present some related works; in Section 3, we discus intrusion detection in mobile devices; in Section 4, we provide our assessment methodology; in Sections 5–6, we discuss the results of our evaluation; in Section 7, we present a set of guidelines that would help researchers to avoid common pitfalls and improve the quality of their work. Finally, we summarize our conclusion in Section 8.

2 Related Work

With the recent burst of research interest in the area of smartphone security, a number of studies have been aiming to organize and classify the existing efforts. One of the first attempts to summarize the research in the area of security for mobile devices was presented by Enck [24]. A broader study focusing on a variety of mobile technologies (e.g., GSM, Bluetooth), their vulnerabilities, attacks, and the corresponding detection approaches, was conducted by Polla et al. [33]. A more thorough analysis of research in the area of smartphone related to security solutions was offered by Shahzad [46]. Before these major surveys there were several other studies focusing on various aspects of mobile phone security [49, 19, 30, 12].

The lack of clear guidelines for structuring and analyzing existing research in the area of smartphone security has triggered additional efforts aiming to devise a structured taxonomy and provide necessary classification criteria. Among these efforts, there are a taxonomy for classification of smartphone malware detection techniques proposed by Amamra et al. [12], and a classification of attack vectors for smartphones developed by Becher [17].

To complement these research efforts, several study groups have been surveying mobile malware characteristics. Felt et al. [27] evaluated the behavior of 46 mobile malware samples and the effectiveness of existing defence mechanisms. On a broader scope, Zhou et al. [52] gave a detailed characterization of over 1000 Android malware samples.

This paper, on the other hand, steps beyond traditional survey boundaries and takes a critical look at the experimentation practices adopted by the smartphone security community.

3 Specificity of Intrusion Detection in Mobile Devices

Intrusion detection in traditional networks is one of the most well defined and extensively studied fields. Intrusion detection in mobile networks generally falls under an umbrella of this broader domain, and thus the core foundation of intrusion detection generally follows the defined principles. At the same time, there are several specificities that make traditional IDSs not suitable for mobile devices:

- *Constrained resources*: the resource-constrained environment of smartphones puts strict limitations on the usage on the available time, power, and memory resources, essentially dictating what actions the detection system can and cannot afford. As such many of the approaches that require a heavy computational operations (e.g., malware static analysis) are avoided.
- *Mobility*: As opposed to traditional IDSs where an IDS system is permanently stationed on a known network or a host, mobile device IDSs are generally located on a mobile device with some more resource intensive functionality residing on a cloud. Thus as mobile device goes through a variety of networks with often unknown configurations and different security postures, mobile IDS faces various challenges to provide a comprehensive defense for a wide range of threats and conditions.
- *Deployment environment*: One of the security features characterizing modern mobile platforms is the use of sandbox environment that allows to constrain unwanted activity. Since a sandbox is meant to execute untrusted code, trusted native code is generally run directly on a platform. Although sandboxing is generally seen as a desirable intrusion detection technique, it has limitations. Sandboxing is usually less effective in detecting non-generic targeted attacks, e.g., malware designed to be activated on specific user action or to trigger malicious behavior after a period of normal activity.

  Sandboxing is also largely ineffective against another practice, i.e., the use of external code, that have been gaining popularity in mobile apps. This mechanism allows to use legitimate application to load a malicious functionality without requiring any modifications to the existing legitimate code. As such the original bytecode remains intact allowing an app evade detection. Poeplau et al. [40] defined several techniques to load external code on a device: with the help of class loaders that allow to extract classes from files in arbitrary locations, through the package context that allow to access resources of other apps, through the use of

native code, with the help of runtime method exec that gives access to a system shell, and through less stealthy installation of .apk files requested by a main .apk file.

- *Exposure*: The typical attacks vectors seen in traditional platforms also exist in mobile environments. However, the specificity of mobile devices opened up new avenues for compromise. As such infection methods usually not monitored by traditional IDS, e.g., through SMS, MMS, app' markets, have recently gained a wide popularity.
- *Privacy*: As opposed to traditional networks where privacy leakage typically constitutes a small portions of potential threats, private information theft is rapidly becoming one of the major concerns for mobile devices [32, 44].

4 Evaluation Methodology

To investigate evaluation practices employed by security community, we conducted a survey of research work in the area of intrusion detection for smartphones published since the official release of Android platform in 2008. To avoid selection bias, we collected all research papers indexed by Google Scholar for the reviewed time period from 2008 until 2013. This included studies introducing defence mechanisms specifically developed for the smartphone platforms.

Our research study excluded short papers, extended abstracts, non-peer-reviewed research, and papers not available in the English language. To narrow our focus, we further selected research work relevant to intrusion detection; thus, any methods specifically developed for fault detection, safety analysis, etc. were excluded. The final set of 120 papers, containing 17 journal and 103 conference/workshop papers, was reviewed manually without use of any automatic search techniques. Each of the selected papers were put through at least two evaluation rounds to reduce classification errors.

5 Overview of the Reviewed Studies

In the past several years the number of studies in the field of mobile phone security has been steadily increasing as our survey shows in Figures 1, 2.

Even though most of the research focus on Android, we have seen other platforms used as testing platform as illustrated in Table 1. Traditionally, there have been various classifications relating to intrusion detection mechanisms. Statistics about the surveyed papers with regards to these classifications are

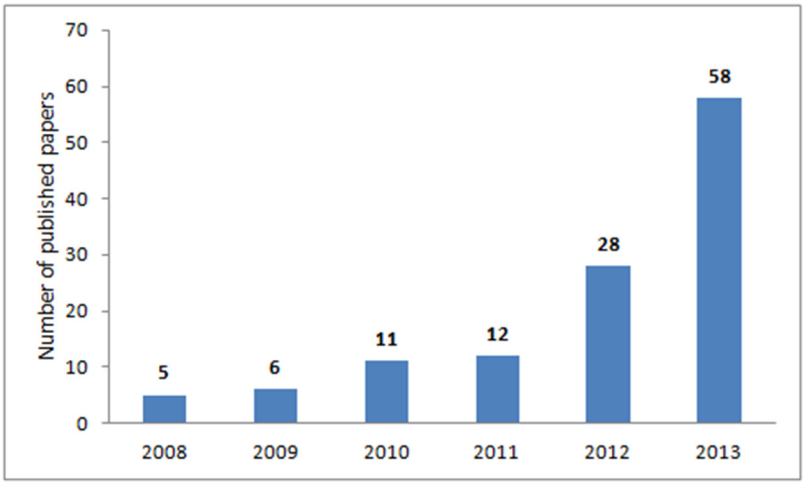


Figure 1 The reviewed papers: a perspective over the years

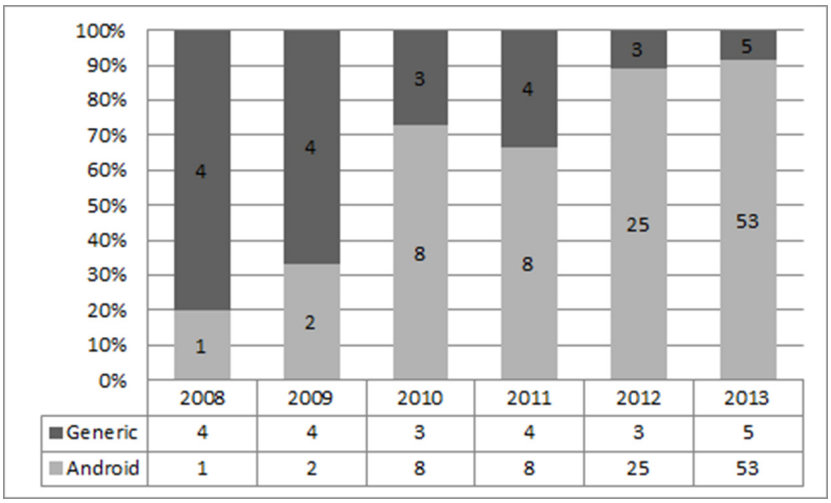


Figure 2 The reviewed papers: a perspective over the years

Table 1 The details of generic approaches

Testing Platforms	
Symbian OS	35% (8 papers out of 23)
Windows Mobile OS	26% (6 papers out of 23)
Hybrid	39% (9 papers out of 23)

Table 2 The details of the surveyed papers

Papers by intrusion detection types	
Network-Based methods	5% (6 papers out of 120)
Hybrid Methods	13% (15 papers out of 120)
Host-Based Methods	82% (99 papers out of 120)
Application level	64% (73 papers out of 114*)
Operating system level	3% (4 papers out of 114)
Hardware level	4% (5 papers out of 114)
Hybrid	29% (32 papers out of 114)
Malware Detection	67% (80 papers out of 120)
By detection approach:	
Anomaly-Based	55% (44 papers out of 80)
Signature-Based	44% (35 papers out of 80)
Hybrid	1% (1 papers out of 80)
By focus:	
Malicious Apps	65% (52 papers out of 80)
Information Leakage	19% (15 papers out of 80)
System Behavior	16% (13 papers out of 80)
Papers by applied detection approach	
Anomaly-Based	58% (70 papers out of 120)
Signature-Based	40% (48 papers out of 120)
Hybrid	2% (2 papers out of 120)
Papers by a level of invasiveness	
Static	35% (42 papers out of 120)
Dynamic	48% (57 papers out of 120)
Hybrid	17% (21 papers out of 120)

shown in Table 2. Among the reviewed papers, the majority of the studies focused on a host-based detection (99 papers out of 120), with only six papers introducing network-based mechanisms and 15 papers proposing hybrid approaches. In addition to these common categories, we noticed an increased interest in specialized mechanisms for mobile malware detection: 80 papers out of 120 considered various aspects of malware detection either through detection of malicious apps (52 out of 80 papers), detection of information leakage (15 out of 80 papers) or suspicious system behavior (13 out of 80 papers).

5.1 Intrusion Detection Focus

To provide a broad overview of research conducted in the field, we categorize the research based on three common parameters: monitoring scope of the proposed technique, underlying detection approach and level of

*114 papers include 99 pure host-based analysis and additional 15 hybrid approaches.

technique invasiveness. Figure 3 illustrates a high-level summary of these categorizations.

By scope of monitoring In general, suspicious activity can be spotted at least at one of the following levels: application, operating system (OS) or hardware. Events at the application level are generally related to user activity and are often seen through suspicious SMS/MMS messages, unusual keystroke dynamics, etc. Since this is a high-level behavior that is not necessarily exhibited by all malware threats, a placement of detection mechanisms at this level provides only limited coverage. OS level activity, on the other hand, includes events triggered by the built-in OS mechanisms (e.g., system calls) thus giving a better picture of the underlying system behavior. While this is often a preferred location for intrusion detection mechanisms in traditional computer-based environments, it presents a number of problems for resource-constrained mobile phone environments that can only afford lightweight detection techniques. Finally, intrusion detection at hardware level allows researchers to obtain basic measurements of the monitored systems (e.g., CPU, network usage, power supply) that might be indicative of abnormal device behavior, especially when they are compared to normal device usage.

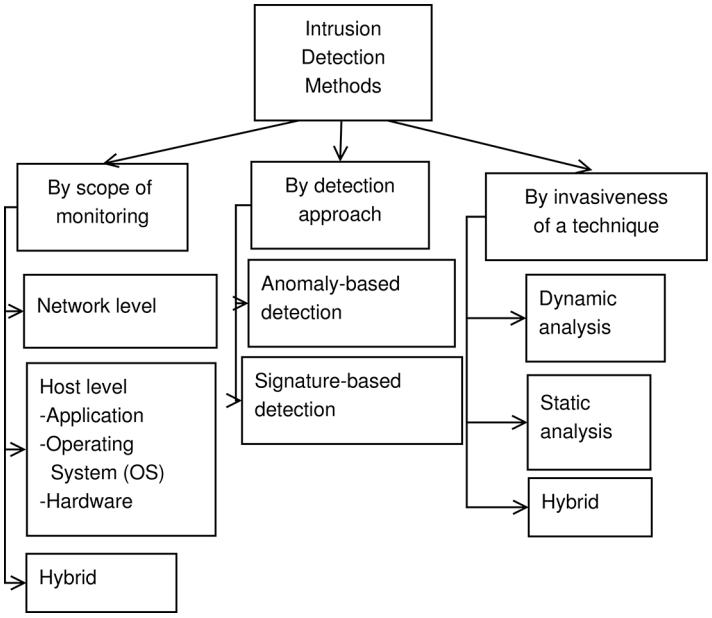


Figure 3 Overview of intrusion detection methods classification

Detection at this level provides a number of benefits that are particularly valuable for mobile devices, including fast, reliable, and scalable intrusion detection. Of the reviewed papers, the majority of studies focus on application level (64%), then OS level (only 3%), and then hardware level (4%). The remaining papers address hybrid levels (29%).

By detection approach Another common classification of intrusion detection techniques, based on how intrusive activities are detected, broadly groups techniques into anomaly-based and signature-based approaches. Since anomaly-detection is perceived as more powerful due to its higher potential to address new threats, it is not surprising to see the majority of the reviewed studies employing it (70 papers out of 120).

Interestingly, a large portion of the reviewed studies is focused on the application of signature-based detection. In spite of criticism of this approach in academic research (due to a high reliance on ever-growing signature bases and the lack of detection of 'zero-day' threats) almost 40% of the reviewed studies (48 out of 120) employed signature-based detection.

By invasiveness of technique The approaches for detection of intrusive activity can be further broken down into dynamic (behavior-based) and static detection, depending on the level of invasiveness of the intrusion detection system. Dynamic techniques generally adopt a black box approach by focusing on behavior of a target system in general or specific files/apps in particular. Since this detection is only possible during the execution of a program, it has a limited focus and is often at the mercy of the executable malware that might or might not exhibit suspicious behavior in a given running environment. Static detection, on the other hand, allows the researcher to analyze an app/file without its execution (via disassembly or source code analysis) and is thus considered to be more thorough, although it is more expensive. Among the reviewed studies, 48% of the papers employed dynamic analysis, with 35% focusing on static detection.

5.2 Trends

The vast popularity of mobile phones, and specifically the Android platform resulted in a rapid increase of mobile malware. One of the major sources of malware became third party app markets [29, 52]. For example, due to popularity of Android platform, we have seen a arise of alternative Android app markets (i.e. not officially supported by Google), often known for their lack of security checks and thus favored by malware writers. Figure 4 clearly shows this trend. Although the use of Google Play market slightly increased

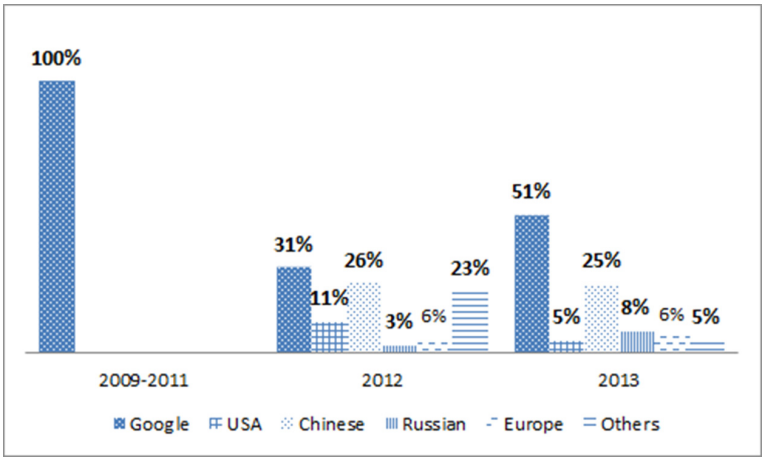
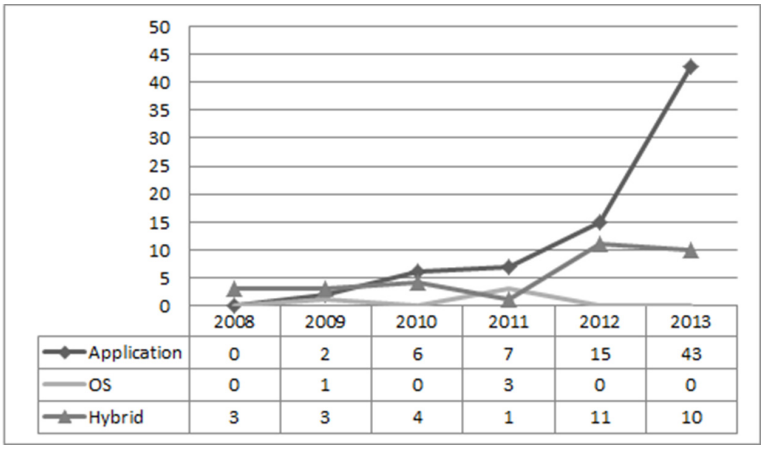


Figure 4 The use of apps from various markets in the surveyed works



	2008	2009	2010	2011	2012	2013
Application	0	2	6	7	15	43
OS	0	1	0	3	0	0
Hybrid	3	3	4	1	11	10

Figure 5 Trends of Research Focused

from 2012 to 2013, it has a significantly smaller share compared to the newly-emerging markets.

Among other trends noticed in the reviewed studies is a clear tendency towards application-level detection (Figure 5). The interest in application-level detection has been steadily increasing and in 2013 the proportion of studies with this scope reached 64%.

6 Detailed Survey Observations

The impact of data quality on the outcomes of the various studies was emphasized throughout the research. Indeed, the ability of a study to predict the performance of a method in a real deployment environment is highly dependent on the ability of a dataset to reflect conditions of that deployment setting.

Datasets. Although the mobile phone setting is not an exception, the lack of comprehensive datasets (mostly attributed to immaturity of the field) has posed a significant problem [52]. There have been several attempts to create structured, comprehensive datasets specifically for evaluating mobile security solutions. Table 3 lists some of these publicly available resources. In spite of their variety, most of these sets have limited applicability and/or require additional preprocessing. The lack of appropriate datasets is reiterated throughout the papers in our survey: all papers that involved experimental studies (110 out of 120 papers) employed self-constructed datasets (see table 4). Although the researchers' intentions are understandable, the lack of standardized datasets employed across the majority of studies raises several concerns.

The first concern is the transparency of a dataset. Customized datasets require collecting data, preprocessing activities (e.g., anonymization, cleaning out redundant data, assuring necessary balance of normal and suspicious behavior), and validating (e.g., confirmation of 'ground truth'). These activities are tedious, time-consuming and often require specialized infrastructure, including equipment and necessary permissions for collecting private data. Unless these activities are fully described and the dataset made available, there is little assurance that a dataset will be representative of a deployment environment. Although the initial step can be avoided with the use of malware repositories, the rest of the concerns remain.

Due to the nature of smartphone threats, the authors of all 110 papers that conducted an experimental study employed a set of mobile apps for this analysis. Out of these 110 papers, 91 papers used real apps collected through app markets and online mobile repositories, three papers implemented their own version of apps and five papers used a combination of these two categories (real and self-written apps).

The majority of the real apps used in surveyed papers were collected through various Android markets (58% of papers) with the assumption that apps coming from a market are benign. With the increasing number of reports showing markets being adopted by hackers as one of the ways for malware distribution, it is expected that all market apps in any experimentation study

Table 3 The existing sources of data for evaluation of mobile security solutions

Name	Institution	Description	Access	Size	Fixed	Labeled	Year	Platform
MIT Reality mining dataset [23]	MIT Human Dynamics Lab	Data collected on smartphones on users' location, communication and device usage behavior for over 9 months; includes only normal user behavior.	Free registration	–	Yes	Yes	2005	Collected on Nokia platform
Android Malware Genome Project [52]	North Carolina State University	Collected malware samples from 49 representative Android families.	Academic registration	1260 samples	Yes	Yes	2011	Android
Mobile Malware in the wild dataset [27]	University of California, Berkeley	Collected malware in the wild from 2009 to 2011	Public Information, not samples.	46 samples	Yes	Yes	2011	iOS, Symbian, Android
Contagio mobile [4]	Personal	Digital place to share mobile malware samples and Analysis, based on a centralized community effort.	Public	330 samples	No	Yes	2011	All mobile
Google group mobile. malware [8]	Community effort	A mailing list for researchers in mobile malware field. Contains material related to new mobile malware samples, analysis, new techniques, questions pertaining to the field, and other related data.	Free registration	–	No	Partially	2010	iOS, Android, Symbian, Windows mobile

AndroMalShare [1]	Xi'an Jiaotong University	This project focuses on sharing Android malware samples. A sampled scanned by SandDrois and provides a detailed report and detection results from several anti-virus tools.	Academic registration	8745 samples	No	Yes	2013	Android
VirusShare [10]	Personal	A personal effort to share samples collected over the years, and accepting contributions from others.	By invitation	–	No	Partially	2011	All type, including mobile
VirusTotal Malware Intelligence Services [11]	Google subsidiary	Free online service for analysis of suspicious binaries and URLs.	Public, only analysis	–	No	Yes	2002	All type, including mobile
SMS Spam Collection [9]	Personal	Collection of SMS messages used for mobile phone spam studies collected by different research groups and by crawling the Internet.	Public	5,574 messages	Yes	Yes	2006–2007	Mobile phones
Android Malware Performance Counter Data [21]	CASTL, Columbia University	Collection of performance counters for Android.	Free registration	–	Yes	Yes	2012	Android ARM

Table 3 Continued

Name	Institution	Description	Access	Size	Fixed	Labeled	Year	Platform
Mining Permission Request Patterns [28]	University of California, Berkeley	The dataset provides the permissions requested by the application., the price, the number of downloads, the average user rating, and a short prosaic description	Public	188,389	Yes	Yes	2011	Android
DroidAnalytics [51]	ANSRLab, Chinese University of Hong Kong	Android malware from 102 different families, with 342 of them being zero-day malware samples from six different families.	Academic registration	2494	Yes	Yes	2013	Android
Drebin [15]	University of Gottingen	Android malware from 176 different families.	Academic registration	5560	Yes	Yes	2010–2012	Android

Table 4 Experimentation practices employed in the surveyed works

Datasets	
Data collection detail:	
Market-Based	52% (63 papers out of 120)
Host-Based	43% (51 papers out of 120)
Network-Based	5% (6 papers out of 120)
Datasets details:	
Self-constructed set	97%(107 papers out of 110)
MIT Reality	3%(3 papers out of 110)
Dataset sharing	3% (3 papers out of 110)
Real apps	83% (91 papers out of 110)
Self-written	11% (12 papers out of 110)
Hybrid	6% (7 papers out of 110)
Normal apps:	
From Market	54% (53 papers out of 98)
Not specified	46% (45 papers out of 98)
Malware samples:	
From Repositories	16% (16 papers out of 98)
From Known Data set	17% (17 papers out of 98)
Hybrid	2% (2 papers out of 98)
Not specified	65% (63 papers out of 98)
Evaluation	
Performed experimental study	90% (108 papers out of 120)
Used simulation	2% (2 papers out of 120)
Do not perform experimental study	8% (10 papers out of 120)
Among 110 that performed experiments:	
Reported evaluation results	93% (102 papers out of 110)
Compared with other techniques	15% (17 papers out of 102)
Involved Internet Access	15% (31 papers out of 78*)
Used Monkey tool	15% (11 papers out of 78)
Employed evaluation metrics:	
Detection Rate	23% (25 papers out of 110)
FPR	35% (39 papers out of 110)
Recall	26% (29 papers out of 110)
Precision	10% (11 papers out of 110)
ROC curves	11% (12 papers out of 110)
AUC	12% (13 papers out of 110)
Self-developed metrics	11% (12 papers out of 110)
DR or FPR or ROC Curves	45% (50 papers out of 110)

will undergo a thorough check to ensure their legitimacy. However, among these studies only 27 verified that apps are malware free.

*78 papers include 57 dynamic analysis and additional 21 hybrid methods.

The other concern related to the use of several sources (i.e., markets) for compiling a single dataset is the necessity of data cleaning. Since many authors distribute apps through a number of markets, duplicative apps (both legitimate and malware) are commonly encountered in different markets. In the reviewed set only 27% of the papers reported at least some activity related to data cleaning.

Although malware apps can be obtained from a number of sources, only 16 out of 98[1] papers utilized existing mobile malware repositories, while several papers reported the use of self-implemented malware apps. With the appearance of research-based mobile datasets, several studies have turned their attention to already prepared data. As such, 17 out of 98 papers used samples from existing malware sets. However, all of these studies have only partially used the datasets, either removing or complementing the existing samples with additional data. This move is another indication of a dire lack of suitable datasets in mobile phone security.

Table 5 presents a summary of the distribution of legitimate and malicious apps in the employed datasets. Throughout our analysis, we observed a very large differences in the sizes of employed datasets. The main concern that this variability raises is the presence of studies with a very small number of samples. Given the availability of data, especially in recent years, evaluations performed on only three malware samples is hardly representative and thus unjustifiable.

The second concern relates to the lack of standardized datasets available to researchers. Among the reviewed studies only three papers made datasets publicly available[2].

Table 5 The sizes of the employed data set in the surveyed papers

Years	Total Size		Normal Samples		Malware Samples	
	Smallest	Largest	Smallest	Largest	Smallest	Largest
2013	8	276016	3	150368	3	12158
2012	6	482514	20	207865	5	378
2011	5	42000	2	13098	3	32
2010	1	2285	30	2285	1	5
2009	240	311	311	311	2	240
2008	4	1000	3	1000	4	7
All years	1	482514	3	207865	1	12158

[1]The 98 papers include 91 studies employing real apps and seven studies using hybrid datasets.

[2]An explicit note about this availability was made in the content of the paper.

The third concern relates to the feasibility of the comparative analysis. Such variability of customized data makes comparative analysis of techniques challenging. Indeed, among the surveyed papers only 15% (17 out of 102 papers) attempted to compare the effectiveness of the developed approach with other methods.

The fourth concern and one of the primary ones when selecting suitable datasets for experiment, is the selection of features that would serve as a basis for analysis. During our survey we extracted 188 unique features used in the reviewed papers. All the papers, even the ones that did not involve the performance of experiments, propose features for analysis. These features were classified according to the categorizations outlined in Figure 6. The statistics for the most commonly employed features are given in Table 6. In spite of 'permissions' being the most commonly used feature throughout the last five years (29% of papers), before that (prior to 2011) 'system calls' was the most popular feature (as illustrated in nine papers out of 22 papers published during 2008–2010). The variability of features in the surveyed research is yet another indication of the immaturity of the field.

Experimentation. Evaluation of the proposed approach is an essential component of any research study in the domain of intrusion detection. Among the reviewed papers, 10 (8%) did not involve any experimentation, while one paper limited its analysis to simulation only. The limitations of simulation in security domain have been repeatedly emphasized in academic studies [13, 39]. Seen as non-exhaustive evaluation technique, simulation does not provide necessary depth of the analysis mostly due to inability to

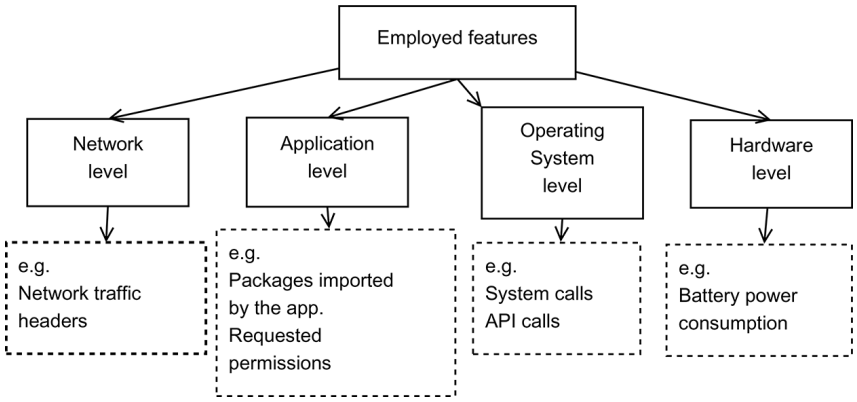


Figure 6 A classification of features

Table 6 Features employed in the surveyed papers

Application level:		
Requested permissions	29%	(69 papers out of 120)
Imported Package	3%	(8 papers out of 120)
Extra information	6%	(14 papers out of 120)
Operating System level:		
API calls	16%	(38 papers out of 120)
System calls	19%	(31 papers out of 120)
Control flow graphs	1%	(3 papers out of 120)
Dataflow	1%	(2 papers out of 120)
Logged Behavior sequences	8%	(19 papers out of 120)
Instructions (Opcode)	6%	(14 papers out of 120)
Hardware level:		
Power consumption	6%	(17 papers out of 120)
Network level level:		
Network traffic	11%	(27 papers out of 120)

guarantee security properties. Constrained to a given scenario simulation does not give insight into a method's performance in unrestricted threat environments or with undiscovered attacks. Although a thorough simulation can provide a sense of average performance of the evaluated technique, it should not be utilized for comprehensive evaluation of security properties.

Among the studies that lacked experiments, only one work reported a proof-of-concept implementation with no mentioning of results. Two of these studies gave a theoretical analysis of the introduced method's performance. Close analysis of the rest of the studies revealed that while all of them discussed some strategies for implementation and potential analysis, none of them offered neither of these.

The details of experimental setup and the employed methodology are necessary to ensure repeatability of the experiments and therefore to facilitate the comparison between techniques. However, as our survey shows most of the researchers neglect to include these details in the study description.

For example, user interface interactions, as one of the triggers of malicious behavior, are known to be essential for analysis of mobile malware [50]. However, among 78 papers that performed dynamic analysis and hybrid analysis of malware, only 11 papers reported the use of user interface interactions to produce events. All of these studies however employed the use of Monkey tool that produces pseudo-random streams of user and system events [14]. Meant for general stress testing of Android apps, the tool is limited to some subset

Table 7 The details of published techniques

Compared with other techniques	
Virus total scanner [11]	23% (4 papers out of 17)
TaintDroid [25]	17% (3 papers out of 17)
Kirin [26]	12% (2 papers out of 17)
Andromaly [45]	12% (2 papers out of 17)
VirusMeter [36]	6% (1 papers out of 17)
Andrubis [35]	6% (1 papers out of 17)
DNADroid [20]	6% (1 papers out of 17)
Androguard [22]	6% (1 papers out of 17)
Clam-AV Scanner [31]	6% (1 papers out of 17)
Manual Analysis	6% (1 papers out of 17)

of actions that do not correctly represent a realistic user of system behavioral patterns.

Similarly, although the access to the Internet is one of the important triggers for many malware, we found that only 31 out of 78 studies reported the use of Internet access in their experiments.

Evaluations. Among the 110 papers that undertook evaluation, eight studies did not report results. Of the 110 studies overall, most works (102) offered experimentation results, which varied significantly from extensive discussion reasoning behind the obtained numbers to a brief mentioning of whether an attack was detected or not.

The evaluation of the method's effectiveness is generally performed along two directions: (1) evaluation of method's overhead in terms of CPU occupancy, memory usage, power consumption and detection speed; and (2) evaluation of the method's detection capability. While both types of experiments are necessary to assess the quality of the newly developed approach, the majority of the surveyed studies are mostly focused on the evaluation of classification accuracy of a method. To assess this accuracy though, it is necessary to compare the new method's performance against known benchmarks in the field. However, due to the infancy of the field such benchmarks are mostly non-existent. As such most of the studies either do not provide any comparison or look at previously proposed methods. Of these surveyed papers, only 17 (15%) compared experimentation results with perviously published intrusion detection techniques and tools. The list of these techniques is given in Table 7. The fact that these techniques are selected for comparison might be an indication of them becoming future benchmarks.

7 Guidelines

The evaluation of intrusion detection methods is an inherently difficult problem due to a variety of factors, from a diversity of monitored events to the unpredictable nature of a deployed environment. Aggravated by the immaturity of the field, evaluation of intrusion detection solutions for smartphone platforms are often guided by subjective choices and individual preferences of the researchers. A review of the experimentation practices employed in this field suggests several important points. Based on the results of our review we formulated several guidelines for proper evaluation of intrusion detection methods for smartphones.

The resulting criteria is offered in three general dimensions of scientific experimentation, formulated by previous research [47, 43]: factors related to *the employed datasets*, *the performed experiments*, and *the performance evaluation*. Since the previous studies have attempted to outline some of the limitations and constraints of scientific experimentation in computer security, we aimed to devise comprehensive guidelines and recommendations for a smartphone setting. The following guidelines can be used as a structure for experimental design and subsequently in manuscript organization:

Employed datasets define applicability and deployability of the developed technique to a real-life setting. To ensure the effectiveness of these qualities the dataset description is an essential component of any manuscript. Although this description will vary depending on the source of data (self-constructed or publicly available), it should provide enough detail to allow an intelligent analysis of the proposed technique. Specifically, the following aspects of employed data should be addressed:

- Data overview:
    - the source of the data, (i.e., whether the dataset is public, proprietary, or self-constructed).
    - quantitative description of malicious and normal events in a dataset (e.g., apps, malware, network flows).
    - how these malicious and normal events were obtained (i.e., simulated, implemented, collected). This should include description of the environment/process. For example, assuming the dataset includes Android apps that are collected from various sources: are these apps free or paid, what are the sources (e.g., list app markets), what malware families these apps represent, why these malware apps are selected while others are excluded? On the other hand, if

the data is collected on the network, then the description should include the duration/time of the collection, access to the Internet, use of visualization, etc.
    - monitored features.
- Data validation:
    - the ground truth established, (i.e., how the legitimacy and abnormality of data is verified). For example, in the case of Android apps, whether or not the collected apps checked through third-party sources.
    - obsolete data removed, (i.e., in the case where a dataset containing malware or apps is employed, sinkholed or inactive samples should be removed).
- Training/testing data:
    - quantitative division of dataset into training and testing sets, corresponding numerical estimation of normal and malicious samples in each.
- Data sharing:
    - data employed in the experiments should be archived for reference for future authors. Even if datasets are not made public, the possibility of sharing on demand should be explicitly indicated in a manuscript.

The performed experiments refer to the setting of the performed experiments and thus allow for transparency of the experiments to be ensured, (i.e., that the conducted experiments are repeatable and comprehensible). Several aspects need to be addressed here to allow for objective evaluation of a study:

- Environmental setting:
    - experimental setup, (i.e., simulation, emulation, experimentation).
    - context for execution for both victim and attack side, including hardware (e.g., devices employed, their topology) and software (e.g., operating systems, NAT, privileges). This description might be complemented with a diagram to avoid ambiguities in interpreting an environmental setup.
    - the employed tools, with an indication of their releases and versions, and parameters.
    - the use of technology (e.g., access to the Internet).

- Experiments:
  - methodology, (i.e., steps involved, allowed user interaction, duration, number of repetitions).
  - the use of sampling, the employed algorithm and justification.

Performance evaluation. The primary goal of this section is to give insight into a proposed method for performance, which is called for a detailed and, more importantly, objective analysis of evaluation.

- Evaluation Methodology:
  - the scripts or procedures used for analysis should be specified. Often a closer analysis of intrusion detection results call for a manual examination of traces. Regardless of the findings this should be stated.
  - the employed statistical apparatus.
- Evaluation metrics:
  - define evaluation metrics. To avoid ambiguities in metric interpretation, a clear definition of a chosen metric should be provided. This becomes critically important when non-traditional metrics are employed, as the lack of consistent terminology hinders researcher's ability to properly identify and apply common methods. As the use of self-developed metrics becomes more widespread, a metric definition should be followed by a clear validation of the proposed metric for a given task.
  - ensure a proper combination of metrics. Detection rate (DR) and false positive rate (FPR) (or their graphical representation ROC curve) are the most widely used metrics in spite of criticism. Several studies have shown that the ROC curve alone or DR/FPR metrics combination might be misleading or simply incomplete for understanding the strengths and weaknesses of intrusion detection systems [18, 48, 38, 16, 34]. Although such misinterpretation can be partially avoided when DR/FPR values are complemented with the absolute numbers of false alarms or missed detections, exclusive evaluation of an approach with these methods may not accurately represent the performance of the system.
- Findings:
  - provide numerical results. The reporting of numerical results should be comprehensive (i.e., use complementary metrics that show all

perspectives of the evaluated method performance) and consistent (i.e., reported in the same equivalents). For example, only stating the accuracy of the proposed approach (i.e., that shows the percentage of correctly classified events) gives almost no insight into a method's performance with respect to malicious events. On the other hand, for example, stating detection rates in percentages, while indicating false positive rates in absolute numbers, makes it challenging for a researcher to interpret the numbers.

- interpret the results. The intrusion detection community has traditionally focused on understanding the limitations of detection methods. Therefore, simply stating numbers is not sufficient for interpreting the performance of the detection method. Numerical results should be included to show the soundness of the approach and allow for future comparative analysis of the detection methods, but they are not the main goal. Thus, a close and often manual examination of results (e.g., false positives and false negatives) is necessary to understand and explain to the research community why and when a system performs in a given way.

- Comparison:
  - a comparative analysis of the proposed scheme with the established benchmarks in the field is an essential component of a study. Whenever existing benchmarks are not available an attempt should be made to perform a quantitative comparison against prior results.

8 Conclusion

With the popularity of Android platform, the amount of research studies on security of smartphones is rapidly increasing. While an increasing volume of studies in the field is generally seen as an indicator of a field evolution, the true value of existing work and its impact on the smartphone security progress remains unclear.

As such in spite of variability of tools proposed only a few of them have been accepted by a security community. Among them is an Android analysis tool, Androguard [22]. Effective against even obfuscation techniques, Androguard has been adopted many academic and industry malware analysis solutions, such as Virustotal portal [11], APKInspector [3], Marvinsafe [7], Anubis (Andrubis) [35], Androwarn [2], googleplay-api [5] and MalloDroid [6]. In academic studies, as our review shows, there is less

consensus and studies employ a variability of tools for evaluation of new solutions.

The validity of experimental research in academic computer science in general has shown to be questionable. Through our review we also confirmed our initial hypothesis, showing that immaturity of the smartphone security negatively affects experimentation practices adopted in the field. In this context, it is plausible to suggest that the lack of adoption of the developed innovations by industry can be attributed to the lack of proper rigor in experimentation that shadows the true value of the developed solutions. Among the factors that contribute to the lack of scientific rigor in experimentation are the lack of consistency and transparency in the use of datasets, the lack of clear understanding of relevant features, the lack of benchmarked experimentation, and the biased selection of malicious apps for analysis.

While the infancy of the field of mobile phone security might justify some shortcomings in experimentation, many of the pitfalls can be avoided with proper practices established and adopted by a security community. To facilitate acceptance of this practice, we formulated a set of guidelines for a proper evaluation of intrusion detection methods for smartphone Platforms. The suggested guidelines allow a detailed description and analysis of experimentation results, and, as such, might be used for designing experimentation studies as well as for structuring experimentation sections in a manuscript. While some of the suggested guidelines might be seen as common sense, we believe that framing them in a structured way will help researchers to improve experimentation practices by providing them with a methodological reference.

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[6] Mallodroid. http://www2.dcsec.uni-hannover.de/files/android/p50-fahl.pdf.
[7] Marvinsafe. http://www.marvinsafe.com/.
[8] Mobile malware forum. https://groups.google.com/forum/?fromgroups=#!forum/mobilemalware.
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Appendix

List of the Reviewed Papers

Android Platform:	
Malware Detection	[1, 2, 3, 4, 5, 7, 8, 9, 10, 11, 12, 15, 16, 17, 20, 21, 22, 23, 25, 27, 28, 29, 30, 31, 34, 36, 38, 39, 40, 41, 42, 46, 48, 50, 51, 52, 53, 54, 56, 57, 58, 59, 60, 61, 62, 64, 65, 67, 68, 70, 71, 72, 75, 76, 77, 78, 80, 87, 93, 94, 95, 96, 98, 99, 100, 102, 104, 105, 110, 111, 116]
NIDS-HIDS	[6, 13, 43, 45, 47, 49, 69, 73, 85, 106]
NIDS	[35, 44, 66, 9]
HIDS	[14, 26, 32, 37, 63, 74, 79, 84, 86, 92, 101, 103]
Symbian OS:	
Malware Detection	[82, 107, 109, 112, 115]
HIDS	[108, 117, 119]
Windows Mobile OS:	
Malware Detection	[83, 89]
NIDS-HIDS	[118, 120]
HIDS	[88, 113]
Other Platforms:	
Malware Detection	[18, 90]
NIDS-HIDS	[24, 33, 55]
NIDS	[19, 81]
HIDS	[91, 114]

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